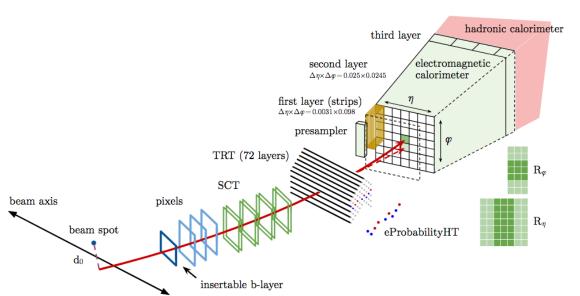




## Visualizing Electrons in ATLAS

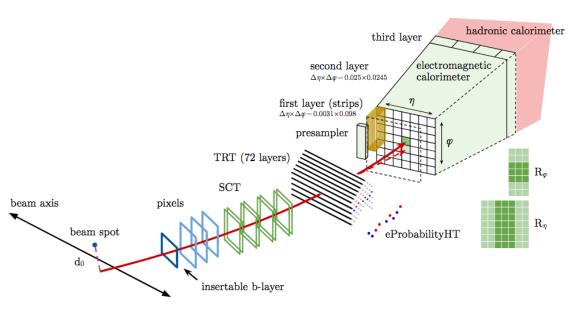
## Electrons In ATLAS



#### **BASICS**

- Electrons are massive and charged → they interact with the tracker and calorimeter
- Create tracks and energy clusters → easy to reconstruct
- Interactions are well understood → can estimate energy well

## Electrons In ATLAS

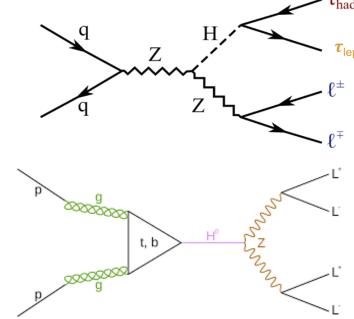


#### **USE IN ATLAS**

- Efficient triggers and ID → analyses with electrons benefit from improved background rejection
- O Accurate reconstruction → final states with electrons have reduced systematics
- Extending the range of electron algorithms → more physics searches are possible
- o But room for improvement!

#### **BASICS**

- Electrons are massive and charged → they interact with the tracker and calorimeter
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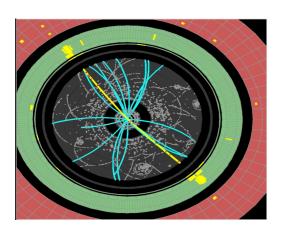


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## Electron Software

#### Reconstruction

- Create clusters from energy deposits in EM Calo
- Create tracks from hits in the inner detector
- Form electron candidates by matching tracks to clusters
  - Based on energy, location, and hit types



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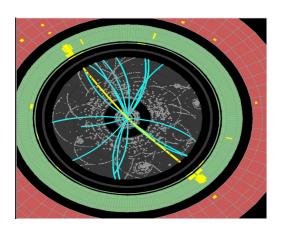
## Electron Software

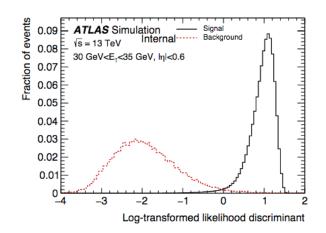
#### Reconstruction

#### Identification

- Create clusters from energy deposits in EM Calo
- Create tracks from hits in the inner detector
- Form electron candidates by matching tracks to clusters
  - Based on energy, location, and hit types

- Calculate physics motivated variables
- Calculate Likelihood
  - Formed from PDFs of electron variables
- Evaluate LH score compared to recommendations





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## Electron Software

#### Reconstruction

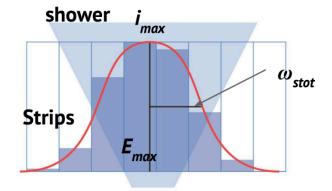
#### Identification

#### **Energy Regression**

- Create clusters from energy deposits in EM Calo
- Create tracks from hits in the inner detector
- Form electron candidates by matching tracks to clusters
  - Based on energy, location, and hit types
- 0.09 ATLAS Simulation Signal Background
  0.08 \( \sigma = 13 \text{ TeV Internal} \)
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  0.07 \( \sigma = 13 \text{ TeV Internal} \)
  0.06 \( \sigma = 13 \text{ TeV Internal} \)
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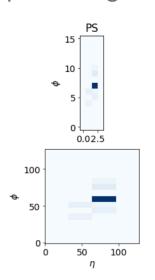
- Calculate potential loss due to bremsstrahlung
- Consider cluster width variability and electronics gain
- Combine effects to get corrected electron energy

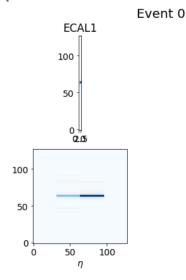


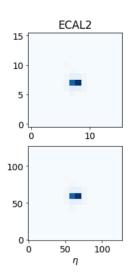
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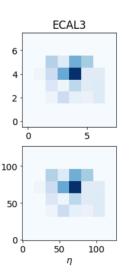
## A New Way to Look at Electrons

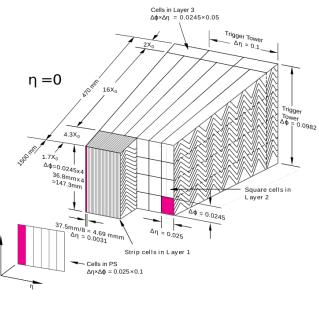
- Most electron algorithms currently combine calculated variables
  - MVA techniques can exploit smaller differences in distributions
  - But potential for information loss is still present
- We could instead look at direct read-outs of the detector
  - One way to represent this information is images ...
  - Consider 'unrolling' the calorimeter and representing cells as pixels





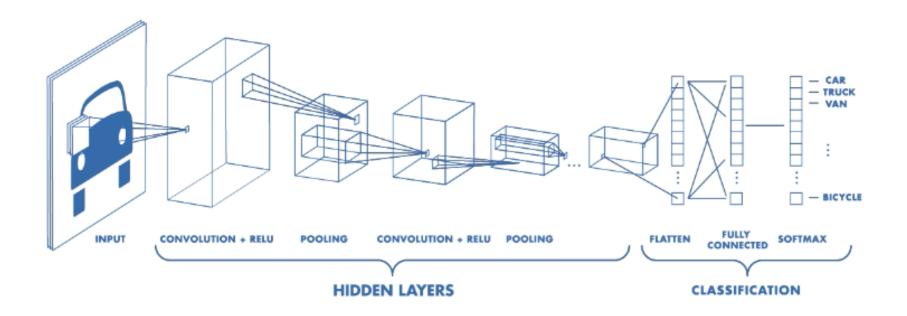






## Computer Vision

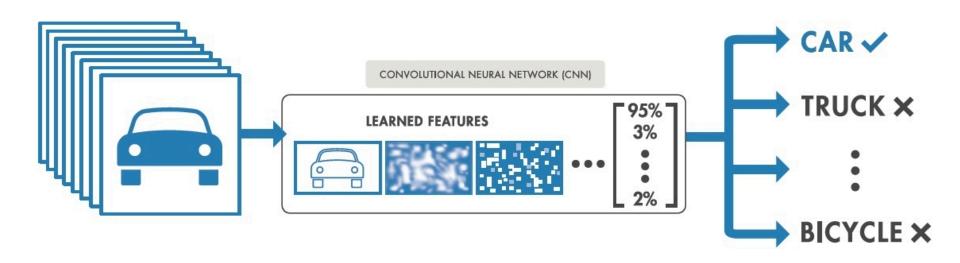
- Convolutional Neural Networks (CNNs) are a popular ML technique for processing images
  - 1. 'Read in' images as a matrix of pixels with numerical values
  - 2. Convolve the image with filters to create multiple high-level representations of the original image
  - 3. Use these representations as input to classification or other task



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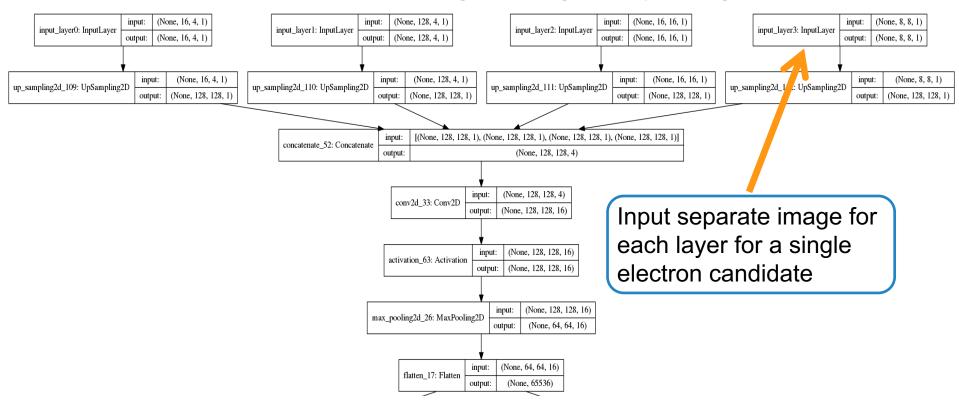
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  - 3. Use these representations as input to classification or other task
- Different filters learn different features/aspects of the image

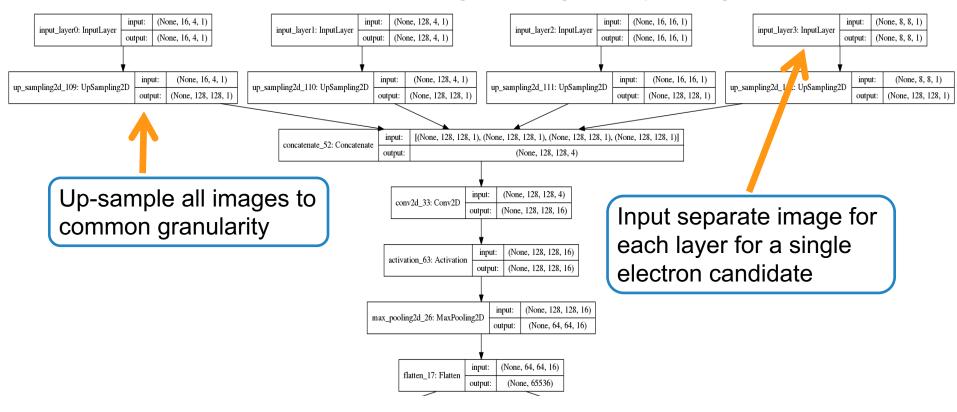


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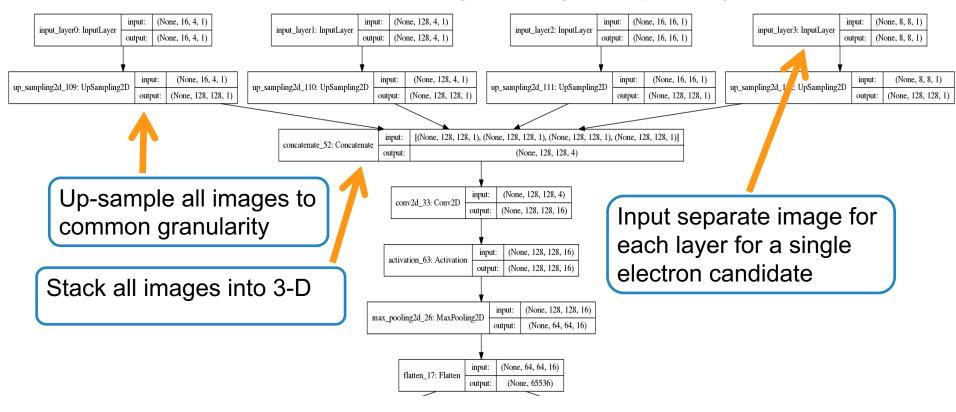
#### Initial architecture design utilizing all 4 layer images



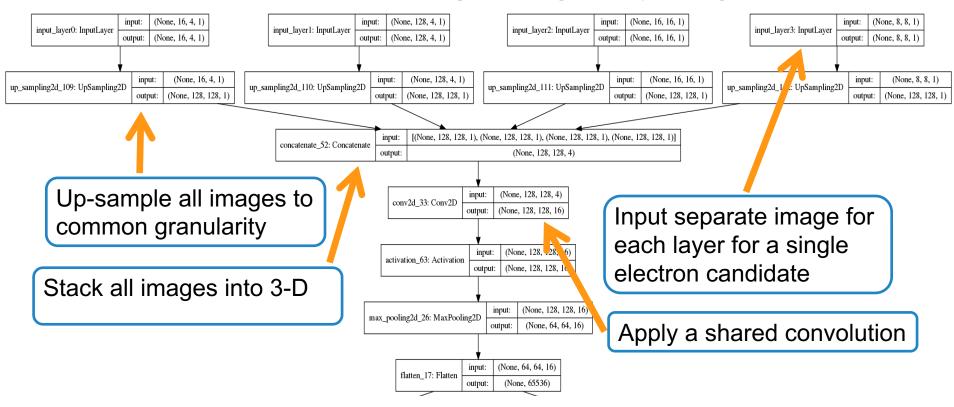
#### Initial architecture design utilizing all 4 layer images



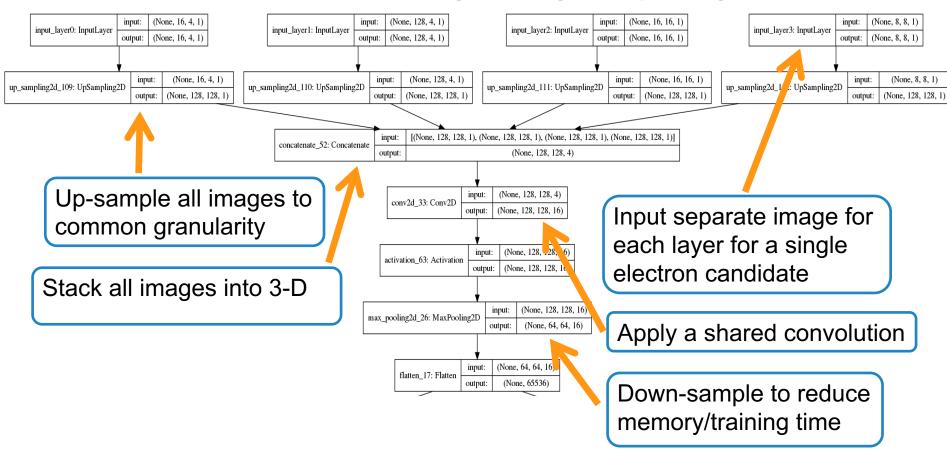
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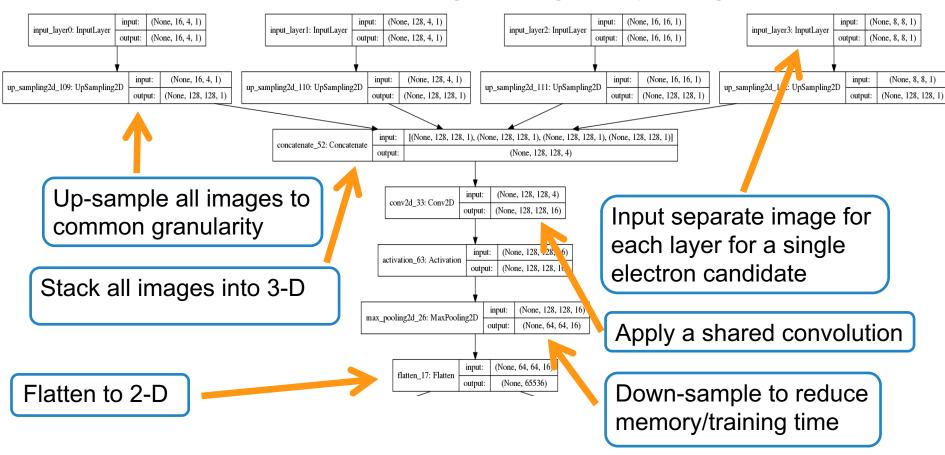
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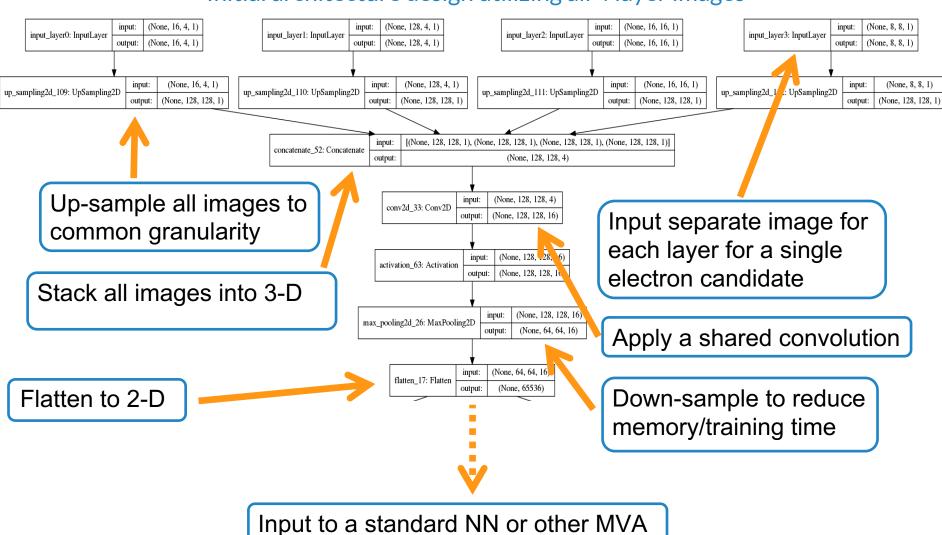
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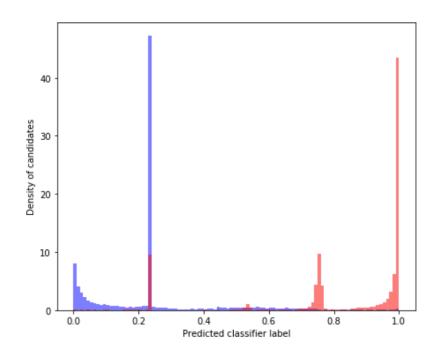


#### Initial architecture design utilizing all 4 layer images



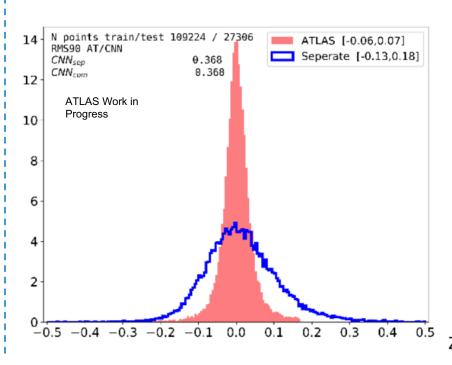
#### **IDENTIFICATION**

- Input processed images to a fullyconnected NN
- Train NN for binary-classification: electrons=1 background=0
- Promising results with simple design and no tuning!



#### REGRESSION

- Input processed images to a fullyconnected NN
- Train NN to produce scale-factor to apply to reconstructed energy
- Not so great results....37% of ATLAS performance



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## On-going Work

- Consider other architectures:
  - Separate convolutions for each layer (no need to up-sample)
  - 3D convolution (allows network to learn relationship between layers)
- Optimize hyper-parameters and network design
- Explore options for including track information
  - Add variables to fully connected DNN
  - Create track images by projecting hits into 2-D plane
- Evaluate feasibility of training on data
  - o Purity is a concern for data samples, but accurate modeling is a concern for MC
  - Can also use GAN to create better simulations

### Exciting results to come!

# Thanks! Any questions?

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